Appendix 2. Summary of dataset in Eitzel et al. (2020) and description of statistical models used in sensitivity analysis of average annual harvest.

Summary of model parameter sweep dataset

In our parameter sweeps conducted in Eitzel et al. (2020), we ran a total of 499,200 simulations. Below are the distributions of both response variables (average annual harvest and persistence) and the predictor variables (categorical management interventions and rainfall scenarios, continuous management interventions, and continuous underlying variables that had been perturbed by 5% above and below their stated values). For results in this paper that use more than one set of simulations with persistence thresholds chosen randomly between biological and Muonde-determined minima, the predictor variables are distributed in the same way (just multiplied 10 times in frequency), so only one version is reported. For the response variables, see below for both versions.

Persistence (response variable)

Of the 499,200 runs in our analysis, 136,548 (27%) of runs persisted for 60 model years (using the biologically minimal thresholds, as in Eitzel et al. 2020).

When we allow thresholds to vary randomly between biological and Muonde-determined minima randomly in each of the 499,200 runs (a global sensitivity test of the thresholds), and then follow this procedure 10 times (creating 10 different versions of the model outputs), only 26,468 of the 4,992,000 runs persisted all 60 years (0.5%).

Average annual harvest (response variable)

Figure A2.1: Average annual harvest distribution (for biologically minimal persistence thresholds), all data (left) and data from only models which lasted for at least a year, making an average harvest more meaningful (left).

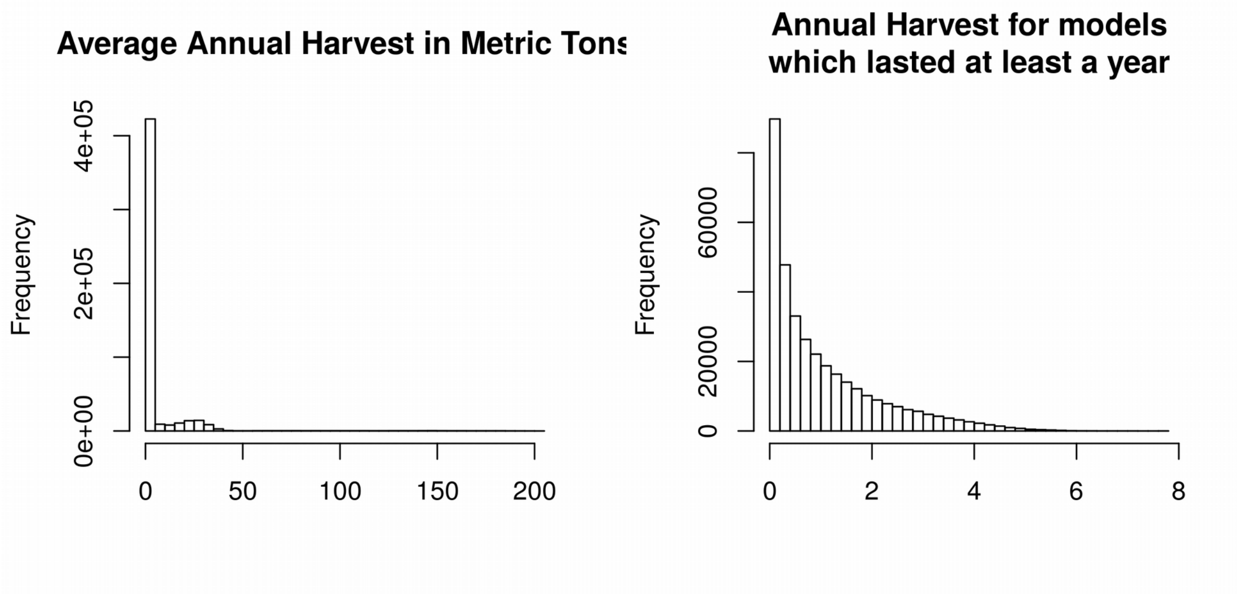
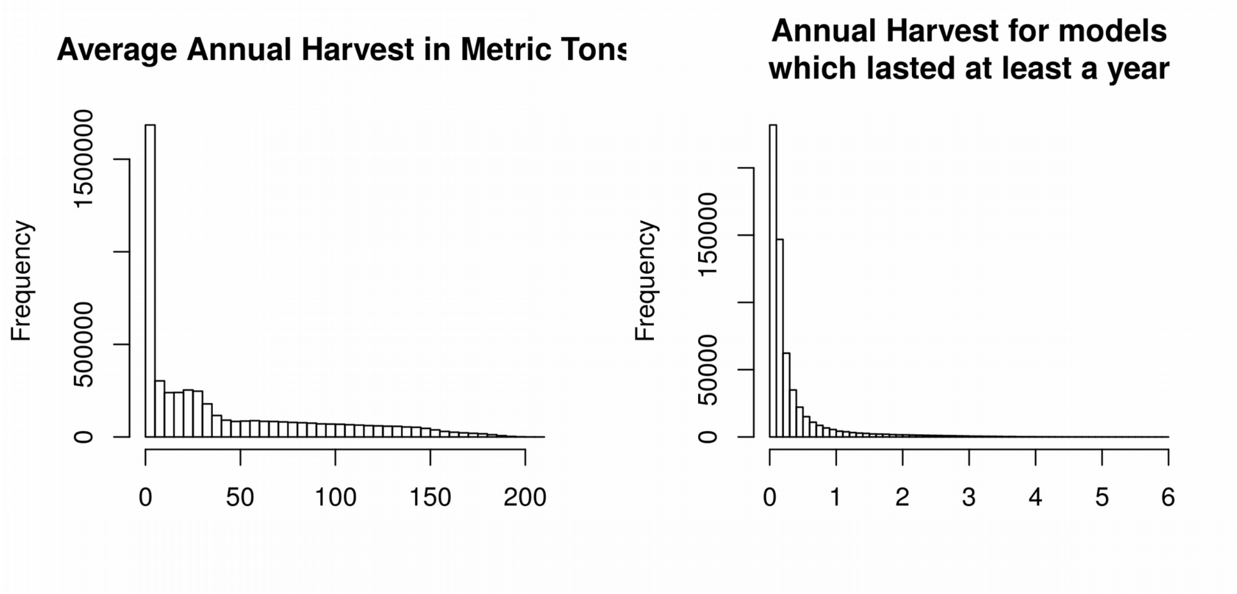


Figure A2.2: Average annual harvest distribution (for the 10 different model datasets with randomly selected persistence thresholds), all data (left) and data from only models which lasted for at least a year, making an average harvest more meaningful (left).



Categorical rainfall scenarios (predictor variables)

Out of all the simulations, the rainfall scenarios were distributed as follows:

Table A2.1: Runs were evenly distributed between different rainfall scenarios using NetLogo's BehaviorSpace tool. "Constant" has fewer runs because subsidy interventions are never used.

Constant	Extreme	Historical	Random	Statistical-extreme	Statistical-random
19200	96000	96000	96000	96000	96000

(Note that the present paper only uses results from the "Historical" and "Statistical-extreme" (high-variation) rainfall scenarios.)

Categorical management variables (predictor variables)

Out of all the simulations, the categorical management variables were distributed as follows:

Table A2.2: Runs were evenly distributed between different management interventions

Subsidize Cows	Move Cows	Stone Walls	Preserve Forest	Crop Innovations	Store Grain
Feed 70%: 96000 Feed all: 96000 Transport 70%: 96000 Transport all: 96000 No Subsidy: 115200	Yes: 249600 No: 249600	Yes: 249600 No: 249600	Yes: 249600 No: 249600	Yes: 249600 No: 249600	Yes: 249600 No: 249600

Continuous management variables (predictor variables)

Figure A2.3: Distribution of proportion-crops variable; this variable ranged up to 97%, hence the short bar at 100.

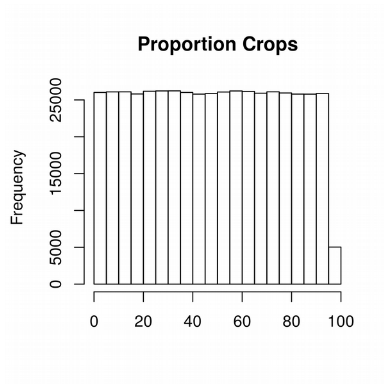
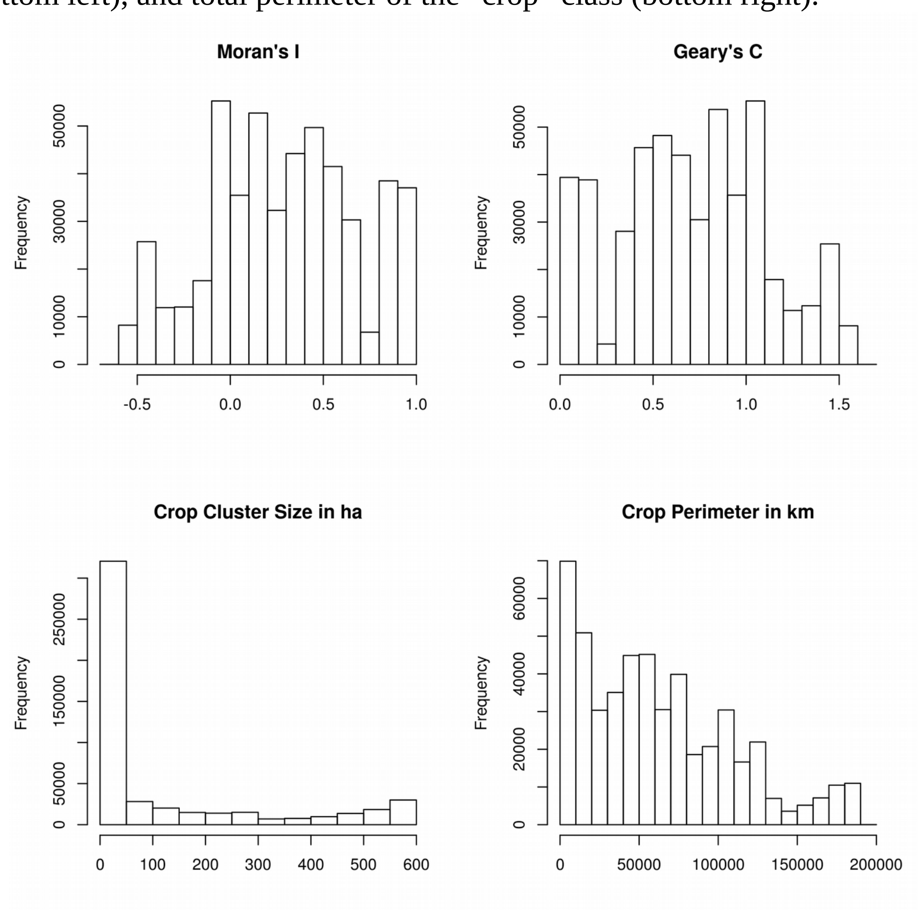
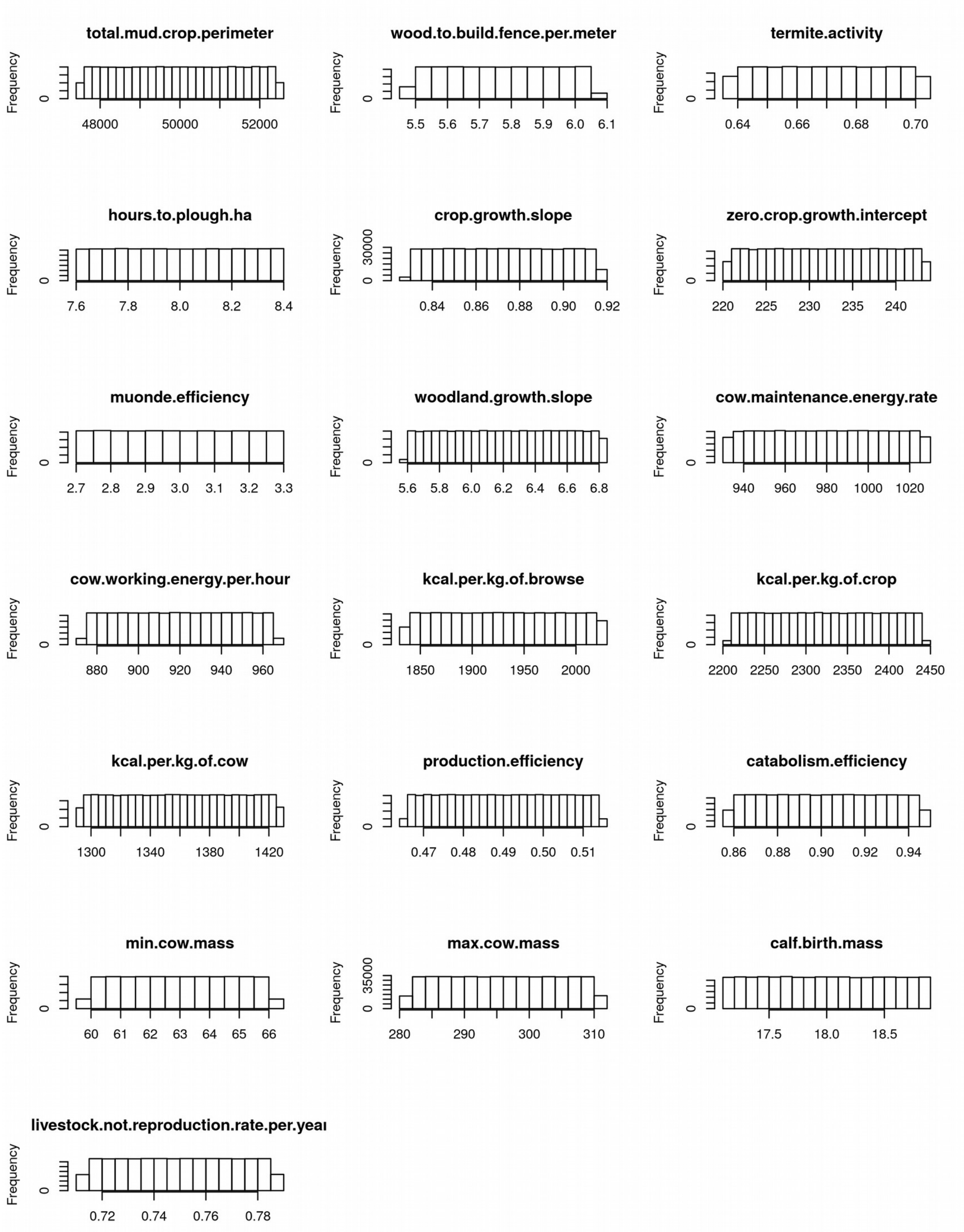


Figure A2.4: Distribution of Moran's I (top left), Geary's C (top right), Crop cluster size in hectares (bottom left), and total perimeter of the "crop" class (bottom right).



Underlying variables (predictor variables)

Figure A2.5: Distributions of underlying parameters, which were perturbed by 5% above and below their stated values.



Statistical sensitivity analysis: Generalized Additive Models (GAMs) of average annual harvest

We used statistical models to compare the relative impacts of different variables while controlling for the others, focusing on effect size rather than exclusively on significance. With a simulation model, the sample size (number of model runs) can be increased to an arbitrarily large number so statistical significance has less meaning. We assume statistical distributions only for the response variables. Many of our simulations had cows, woodland, or harvest below one of the thresholds after the five-year intitialization period (31% of our runs), leading to runs that lasted zero years. The distribution of average annual harvest was therefore zero-inflated, and we used a Tweedie distribution in the GAM estimation process. These distributions are appropriate for zero-inflated, semi-continuous distribution like our harvest variable (Tweedie 1984, Jorgensen 1997). The Tweedie power parameter p was estimated to be 1.788 (between 1 and 2, as expected for a distribution with a point mass at zero and continuous positive values otherwise).

We used GAMs in the “mgcv” package (Wood 2017) in R to test the sensitivity of persistence and average annual harvest to underlying parameters, rainfall scenarios, and management variables. We chose generalized statistical models because the outcome variables are not normally distributed and additive models using smoothing splines because our proportion-crops and spatial configuration variable varied over a wide range of values and a local linear assumption was not appropriate. To represent spatial configuration, we used Moran’s I (Moran 1950) because it is a classic landscape ecology indicator used to represent spatial diversity, and was least correlated with the proportion-crops of the variables we calculated (see above in Figure A2.4 for distributions of other spatial configuration variables).

For sensitivity testing of underlying variables, we used a local linear approximation. We also centered and scaled each of the continuous variables to enhance comparability of parameter estimates and interpretability of the overall model intercept. For the discrete management variables and rainfall scenarios, we used categorical factors. For our outcome variables, we report untransformed parameter estimates in order to compare the magnitude of different model parameters’ influence on model results, but also discuss transformed parameters using the log link. Note that all parameters significant at the $p<0.05$ level are highlighted in bold text. The above analysis is the same as was used in Eitzel et al. (2020) for persistence, with the exception of the Tweedie distribution (for annual harvest) as opposed to a binomial/Bernoulli distribution (for persistence).

Average annualized harvest response variable GAMs

Transformed estimates have had the model intercept added to the estimate before transformation, so annual harvest for that management intervention, rainfall scenario, or underlying variable can be compared with the intercept for the base case with constant rainfall, no management interventions, and average values of all continuous variables (0.776, an annual harvest of 2.173 metric tons, $p<<0.01$).

Note that this appendix uses the names for variables from the NetLogo code; see Eitzel et al. (2018) for definitions.

Table A2.3: Rainfall Scenario parameter estimates for the average annual harvest model (t statistic = 320.22, df = 5, **p<<0.01**).

Rainfall Scenario	Estimate	Transformed Estimate (metric tons)
historical	-0.236	1.716
statistical-random	-0.287	1.632
random	-0.289	1.627
extreme	-0.355	1.524
statistical-extreme	-0.418	1.431

Table A2.4: Management Intervention parameter estimates for the average annual harvest model. See Figure A2.6 for the functional forms for proportion crops and Moran's I.

Management Intervention	Estimate	Transformed Estimate (metric tons)	Degrees of Freedom	t Statistic	p-value
s(proportion.crops)		(Fig A2.1)	8.990†	36376‡	**0.00**
s(morans.i)		(Fig A2.1)	8.993†	1369‡	**0.00**
how.long.to.store.grain3	1.207	7.268	1	80131	**0.00**
muonde.projects10	0.2055	2.669	1	2360.5	**0.00**
subsidy.proportiontransport-0.7	0.07572	2.344	4	62.571	**0.00**
subsidy.proportiontransport-1	0.05584	2.298	4	62.571	**0.00**
invincible.fencestrue	0.055	2.296	1	169.08	**0.00**
subsidy.proportionfeed-0.7	0.02644	2.232	4	62.571	**0.00**
subsidy.proportionfeed-1	-0.01664	2.138	4	62.571	**0.00**
key.resources10	-0.2007	1.778	1	2251.5	**0.00**
times.per.day.farmers.move.cows1	-0.7359	1.042	1	30012	**0.00**

†df is 'effective df', reference df 9.000
‡F-statistic

Figure A2.6: Smooth functions of proportion-crops and Moran's I from the average annual harvest model.

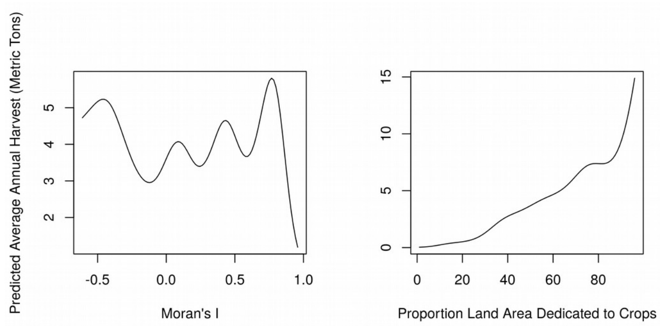


Table A2.5: Underlying variable parameter estimates for average annual harvest model.

Underlying variable	Estimate	Transformed Estimate (metric tons)	Degrees of Freedom	t Statistic	p-value
crop.growth.slope	0.034	1.069	1	251.18	**0.00**
livestock.not.reproduction.rate.per.year	0.025	1.061	1	144.33	**0.00**
muonde.efficiency	0.018	1.053	1	71.25	**0.00**
cow.maintenance.energy.rate	0.009	1.044	1	19.305	**0.00**
cow.working.energy.per.hour	0.005	1.040	1	6.5545	**0.01**
total.mud.crop.perimeter	0.005	1.039	1	5.9519	**0.01**
termite.activity	0.003	1.038	1	2.4822	0.12
kcal.per.kg.of.cow	0.003	1.038	1	2.4752	0.12
hours.to.plough.ha	0.002	1.037	1	1.3486	0.25
min.cow.mass	0.002	1.037	1	1.2402	0.27
max.cow.mass	0.002	1.036	1	0.66224	0.42
production.efficiency	0.001	1.035	1	0.33075	0.57
catabolism.efficiency	-0.001	1.033	1	0.081553	0.78
wood.to.build.fence.per.meter	-0.002	1.032	1	0.55755	0.46
calf.birth.mass	-0.003	1.031	1	1.6416	0.20
kcal.per.kg.of.crop	-0.003	1.031	1	1.9649	0.16
kcal.per.kg.of.browse	-0.006	1.028	1	6.8944	**0.01**
woodland.growth.slope	-0.019	1.015	1	81.558	**0.00**
zero.crop.growth.intercept	-0.021	1.012	1	102.12	**0.00**

We note that for the biologically minimal persistence thresholds, sensitivity analysis of the average annual harvest had different significant underlying biomass-related variables than the persistence variable did (compare with Eitzel et al. 2020), and more of them (12 were significant as opposed to 10 for the sustainability model), but were still mostly smaller in magnitude than the rainfall scenarios and management interventions (except storing grain).

LITERATURE CITED

Eitzel, M. V., K. T. Neves, J. Solera, K. B. Wilson, A. Mawere Ndlovu, A. C. Fisher, A. Veski, O. E. Omoju, and E. Mhike Hove. 2018. Zimbabwe Agro-Pastoral Management Model (ZAPMM): Musimboti wevanhu, zvipfuo nezvirimwa" (Version 1.0.0). *CoMSES Computational Model Library*. [online] URL: https://doi.org/10.25937/ta23-sn46

Eitzel MV, Solera J, Wilson KB, Neves K, Fisher AC, Veski A, et al. (2020) Using mixed methods to construct and analyze a participatory agent-based model of a complex Zimbabwean agro-pastoral system. *PLoS ONE* 15(8): e0237638. https://doi.org/10.1371/journal.pone.0237638

Jorgensen, B., 1997. *The theory of dispersion models*. CRC Press.

Moran, P. A. 1950. "Notes on continuous stochastic phenomena." *Biometrika*, 37(1/2): 17-23.

Tweedie, M.C., 1984. An index which distinguishes between some important exponential families, in: *Statistics: Applications and New Directions: Proc. Indian Statistical Institute Golden Jubilee International Conference*. pp. 579–604.

Wood, S.N. 2017. *Generalized Additive Models: An Introduction with R (2nd edition)*. Chapman and Hall/CRC, New York, USA.